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Intelligent Prediction of Induced Tensile Stresses in Unlined Rock Tunnels Using Artificial Neural Network Under Effect of Explosion Loads

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Abstract

The numerical simulation of explosion in rock mass is extremely demanding, requiring hydrodynamic computer codes, combined with non-linear dynamic codes based on finite elements which is a very complex approach. The Artificial Neural Network (ANN) is used to simulate the elasto-plastic behavior of the unlined tunnel subjected to explosion loads. The simulation was conducted utilizing the original numerical results collected from the AUTODYN program for the vertical-side-wall tunnels. The main aim of this paper is to investigate the induced stresses in rock mass at the tunnel crown under blasting vibrations and the effect of different of rock mass qualities on the wave propagation associated with the explosion. The data base used in the ANNs analysis consists of various values of Rock Mass Rating (RMR), tunnel radius (R), charge weight (W), crown-detonation distance (D) and (W/D) ratio as input data and the values of induced tensile stresses as output data.

Results of the 72 AUTODYN models which simulated the unlined tunnel were used for training and testing the network, respectively. The analysis shows that the predicted values of tensile stresses computed by Artificial Neural Network analysis showed good compatibility with the results of the complicated finite element analysis by average percentage equal to 86%.

Keywords:

Explosion, Blasting, 3D-Simulation, AUTODYN, Rock Tunnels,

Artificial Neural network (ANN), Artificial intelligent (AI).

1. Introduction

Artificial Neural Network (ANN) is a part of the Artificial Intelligence (AI) applications which has recently been used widely to model some of the human interesting activities in many areas of science and engineering. Early applications of ANN in engineering go back to the last eighties, [1].

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The ANN is a new computational technique inspired by studies of the brain and nervous systems consisting of a large number of highly interconnected neurons. The ANN can be used to solve the type of problems, for which we can provide sets of input-output cases but we have neither an equation nor a procedure that helps us to map between the input and output data.

Artificial Neural Networks have been used in a wide range of applications related to Geotechnical engineering, such as, soil dynamic analysis, seismic liquefaction assessment, properties of intact and jointed rocks and design of reinforced concrete structures.

Arunakumari and Latha, used the ANN to predict the stress-strain response of jointed rocks under different confined pressure. Rocks of different compressive strength with different joint properties were considered. The data base for training the neural network is formed from the results of triaxial compression tests on different intact and jointed rocks with different joint properties tested at different confining pressures. Results from the analysis demonstrated that the neural network approach is effective in capturing the stress-strain behavior of intact rocks and the complex stress-strain behavior of jointed rocks, [2].

Lee and Sterling (1992) developed a neural network for identification of probable failure modes for underground openings from prior case history information. The study used the knowledge obtained by the neural network to generate a design tool of a tunnel. They used the network as a part of a knowledge based expert system for assisting with tunnel design, [3].

The ANN is used to simulate the elasto-plastic behavior of the previous analyzed unlined tunnel. The simulation was conducted utilizing the original numerical results collected from the AUTODYN program for the vertical-side-wall tunnels. The multi-layer neural network was used in this study; the network architecture consists of an input layer, an output layer and two hidden layers.

2. Modeling

The data base used in the ANNs analysis consists of various values of Rock Mass Rating (RMR), tunnel radius (R), charge weight (W), crown-detonation distance (D) and (W/D) ratio as input data and the values of tensile stresses output data. These data were used for training and testing the networks according to each individual simulated case. The training data were used for finding the relation between the input and output variables, and the testing data were used for validating this relation for data sets which were not used in network training. Results from ANNs analyses are compared against the original numerical data.

Then, the applicability of ANN models for the efficient prediction of the concerned output data through the other values of input data which were not simulated before with the AUTODYN program.

Nonlinear three-dimensional numerical finite element model was carried out using AUTODYN code to simulate the dynamic response of unlined vertical side wall rock tunnels due to explosion loads. The overall configuration of the three-dimensional finite element model used in this study is shown in Fig. (1). The mechanical properties of simulated rock mass are calculated according to the modified Hoek-Brown failure criterion, [4] and Rock Mass Rating (RMR = 40, 60 and 80) which classify the rock mass quality according to Bianiwaski 1989 as hard, moderate and poor rock [5]. The mechanical properties of the rock for different mass rating which were used in this study are presented in Table (1). This analysis adopts RHT material model developed by Riedel, Hiermaier and Thoma is used to simulate the elasto-plastic behavior of rock mass, [6],[7]. Transmitting boundary is applied at the model boundaries to represent the infinite media of rock mass. The Lagrangian subgrid is used to simulate rock mass and shotcrete lining as a solid elements and joint to joint technique was used to simulate rock-lining interaction. Euler subgrid is used to simulate air and explosive materials. Rock Mass Rating, (RMR = 40, 60, and 80), charge weights, (W = 2500, 7500 and 10000 kg), crown-detonation distances, (D = 5, 10 and 15m) and tunnel radius, (R = 3, 4.5 and 6 m).

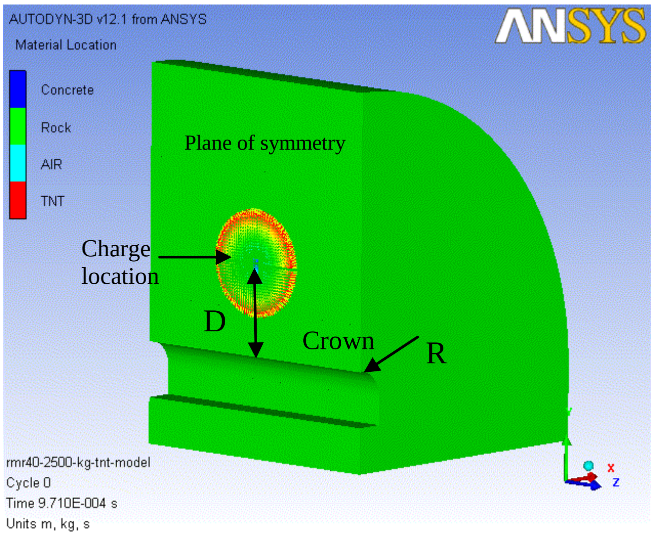


Fig. (1) *Geometry of the numerical model*

Table (1) *Mechanical properties of different Rock Mass Rating*

Rock Mass Rating / Mechanical properties	**RMR 40 (Poor rock)**	**RMR 60 (Moderate rock)**	**RMR 80 (Hard rock)**
Young modulus (MPa)	14.3	50.6	129.5
Uniaxial compressive strength (MPa)	0.285	0.62	4.71
Tensile strength (kPa)	28.5	62	471
Shear strength (kPa)	51.3	111.6	847.8
Unit weight (kN/m3)	24	25	26.5
Bulk modulus (MPa)	11.9	42.1	107.9
Shear modulus (MPa)	5.5	19.5	49.8
Min. strain to failure	0.0075	0.005	0.0025

3. ANN model for tunnel unlined

Results of the 72 AUTODYN models which simulated the unlined tunnel were used for training and testing the network, respectively. Tables (2) and (3) show the used database for network training and testing. The input data include R, RMR, W, D and (W/D) ratio while the concerned output is the induced tensile stress in rock mass at tunnel crown due to

explosion load which will be trained, tested and predicted by using a multi-layer network model [8].
As shown in Table (4) the network architecture designed for the prediction of tensile stresses was chosen after many modeling trails with varying momentum, learning rate, neurons in the hidden layers and epochs based on its lowest training and testing mean standard error for the output variable.

Table (2) *Database for ANN model training (Unlined Tunnel)*

R (m)	RMR	D (m)	W (kg)	W/D	Tensile stress
3	40	5	2500	500	47.4
4.5	40	15	2500	166.67	38.5
3	40	5	10000	2000	12.4
4.5	60	5	7500	1500	54.7
6	60	10	5000	500	111.7
6	40	5	7500	1500	23
4.5	60	10	7500	750	104.5
3	40	10	5000	500	39.6
4.5	60	10	10000	1000	101.6
4.5	40	5	10000	2000	20
6	60	10	7500	750	106.4
4.5	80	5	10000	2000	418
3	80	15	10000	666.67	435.7
3	60	5	10000	2000	33.1
3	40	10	10000	1000	42.7
6	60	5	10000	2000	47.8
6	80	10	2500	250	191.8
6	40	10	10000	1000	16.3
6	40	10	5000	500	47.5
4.5	80	15	10000	666.67	598.7
6	80	10	7500	750	592
4.5	40	5	7500	1500	23.4
4.5	40	10	10000	1000	45.3
4.5	80	10	5000	500	575.2
3	80	10	2500	250	195.4
3	80	10	5000	500	444.4
3	60	10	5000	500	98.2
3	60	5	7500	1500	46.1

6	40	5	2500	500	38.2
3	60	10	7500	750	103.2
4.5	60	5	2500	500	109.5
3	80	10	10000	1000	607
6	80	5	10000	2000	347.5
6	40	10	7500	750	43
3	40	10	2500	250	38
4.5	40	5	2500	500	43
3	80	5	10000	2000	406.13
3	80	5	7500	1500	791
3	60	10	10000	1000	94.7
3	80	10	7500	750	482.1
6	80	15	10000	666.67	680.3
6	60	15	7500	500	109.5
4.5	40	10	5000	500	48.5
6	80	10	5000	500	593.3
6	60	10	2500	250	95.4

Table (3) *Database for ANN model testing (Unlined Tunnel)*

R (m)	RMR	D (m)	W (kg)	W/D	R (m)	RMR	D (m)	W (kg)	W/D
3	40	15	2500	166.67	4.5	60	10	2500	250
3	60	15	7500	500	3	40	5	7500	1500
4.5	80	5	7500	1500	3	40	10	7500	750
6	80	5	2500	500	4.5	40	10	2500	250
6	40	5	10000	2000	6	40	10	2500	250
3	60	10	2500	250	3	60	5	2500	500
6	60	10	10000	1000	4.5	60	5	10000	2000
4.5	80	10	2500	250	6	60	5	2500	500
4.5	60	10	5000	500	3	80	5	2500	500
4.5	40	10	7500	750	6	80	5	7500	1500
6	60	5	7500	1500	4.5	80	10	7500	750
6	80	10	10000	1000	4.5	80	5	2500	500
4.5	60	15	7500	500	4.5	80	10	7500	750
6	40	15	2500	166.67	4.5	80	10	10000	1000

Table (4) *Architecture of ANN model for tensile stress prediction (Unlined Tunnel)*

Number of layers	**4**
Momentum	**0.3**
Learning rate	**0.3**
No. of epochs	**1000**
No. of neurons in 1st hidden layer	**10**
No. of neurons in2nd hidden layer	**10**

Fig.(2) shows the results obtained from ANN analysis which are plotted against the numerical results from AUTODYN, it can be seen that a very good correlation is observed between the two results.

The capability of ANN in capturing the effect of RMR change on the induced tensile stresses due to the applied charge weight located at different crown-detonation distance and different tunnel radius is studied through the designed ANN model for unlined tunnel.

Fig.(3) to (5) show the predicted tensile stresses under effect of different W/D ratio and tunnel radius as RMR changes from 45 to 75 which are plotted through the numerical results for RMR = 40,60 and 80 to make a comparative study for the predicted behavior of rock mass response due to RMR increasing with its behavior which was studied by AUTODYN program.

It can be seen from the figures that increasing of RMR will result the increasing of induced tensile stresses in rock mass at tunnel crown. These results prove that the ANN capable to predict the similar rock mass response as it was studied before by AUTODYN program.

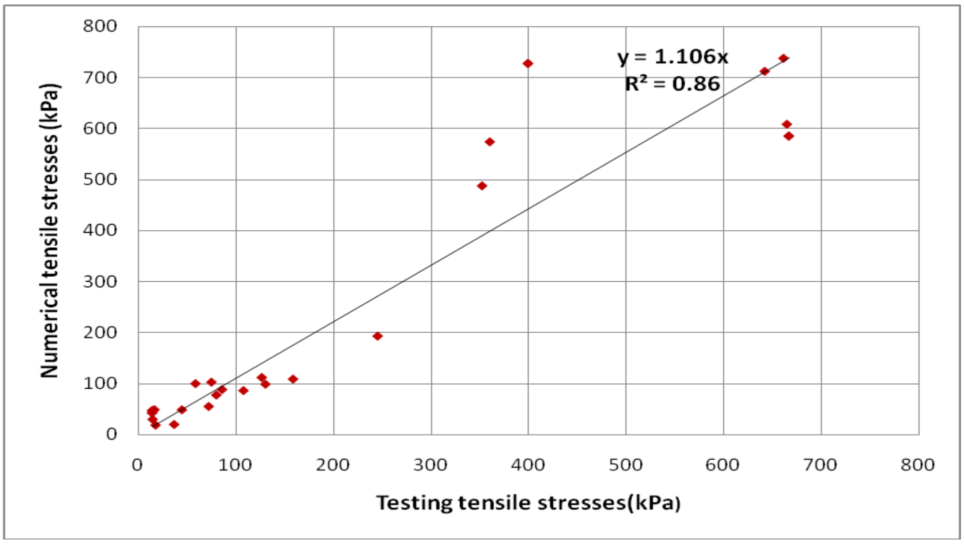
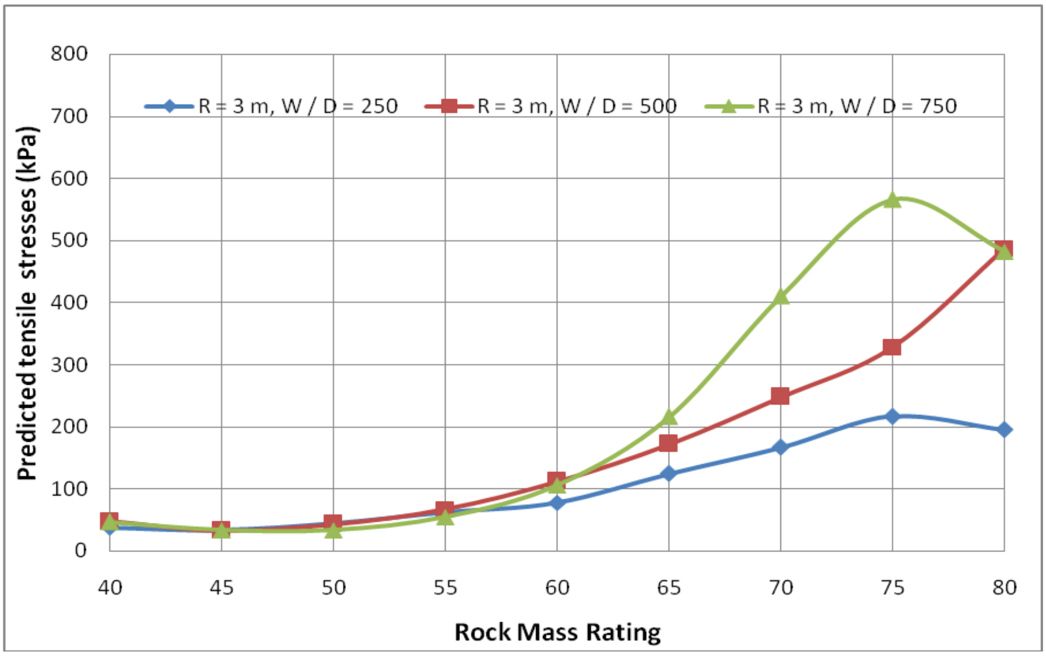
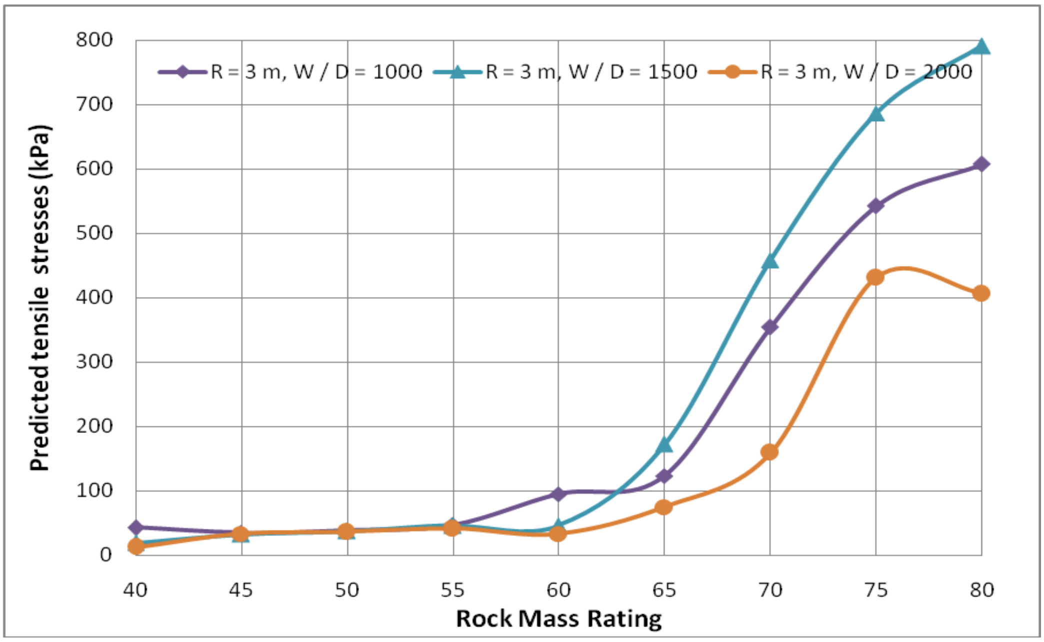


Fig.(2) *Correlation graph between tensile stresses tested by ANN and numerical results by AUTODYN for tunnel unlined*

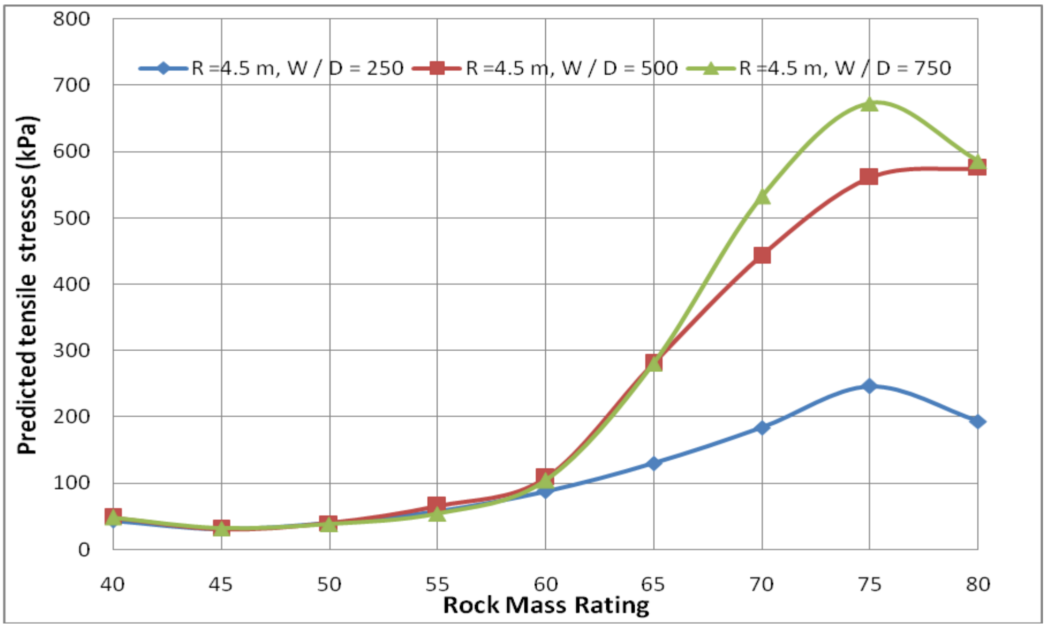


(a)

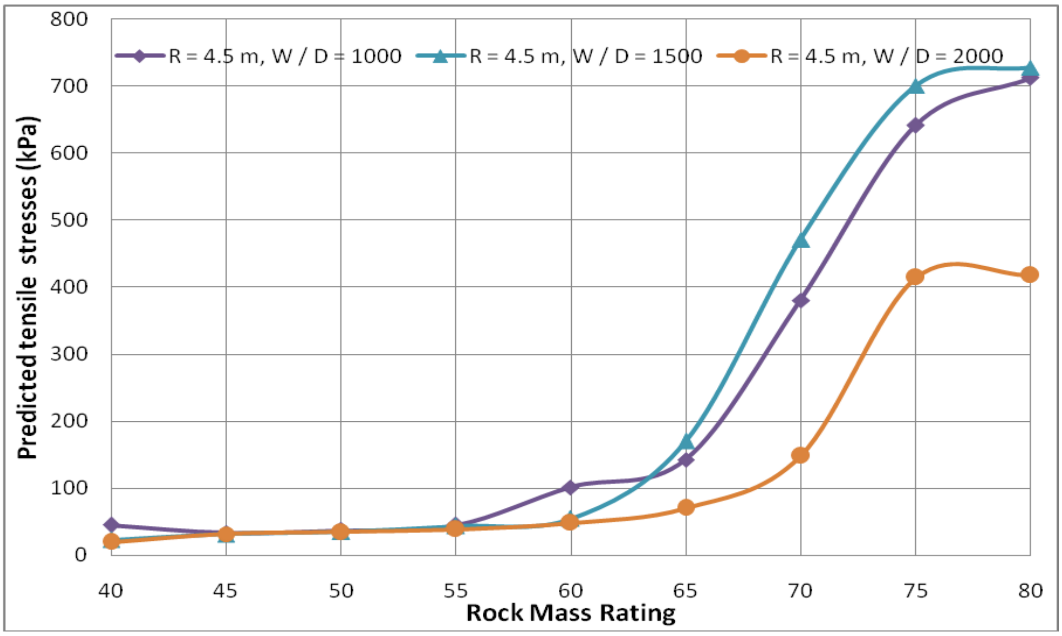


(b)

Fig.(3) *Predicted tensile stresses by ANN under effect of different (W / D) ratio for tunnel radius (R = 3 m)*

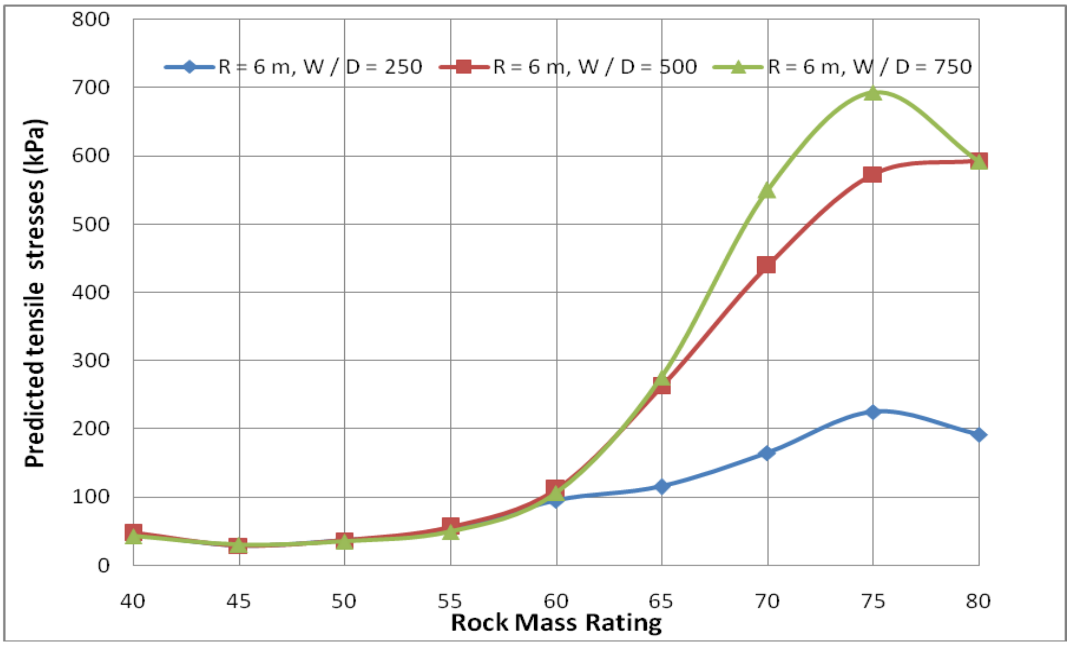


(a)

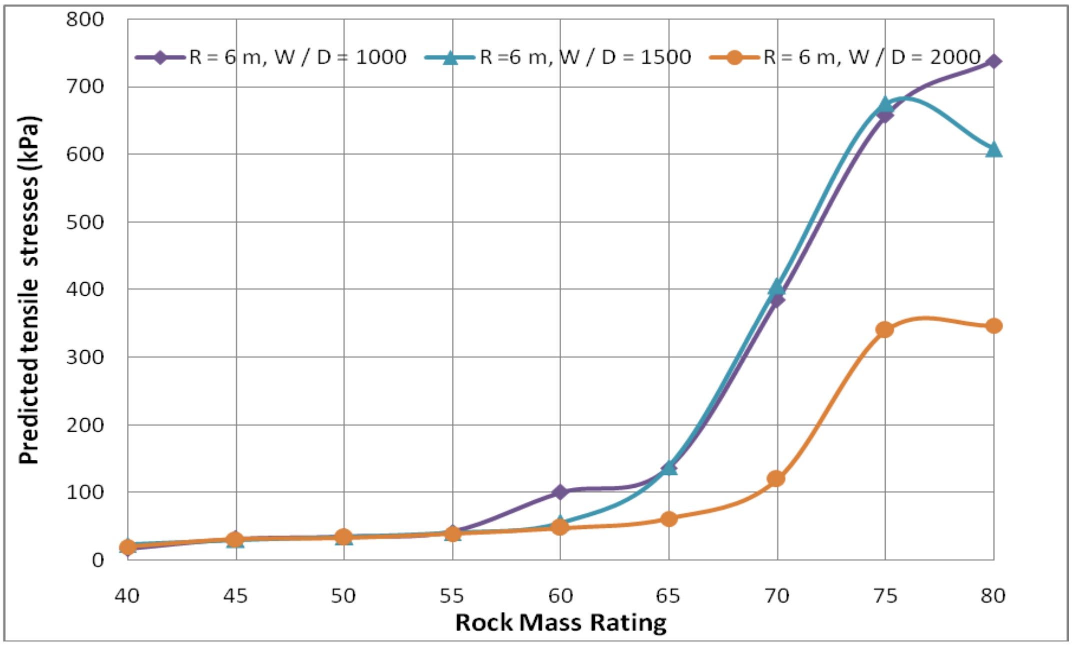


(b)

Fig.(4) *Predicted tensile stresses by ANN under effect of different (W / D) ratio for tunnel radius (R = 4.5 m)*



(a)



(b)

Fig.(5) *Predicted tensile stresses by ANN under effect of different (W / D) ratio for tunnel radius (R = 6 m)*

4. Summary

From this study, neural networks are found to be superior to existing conventional methods in many ways. It was found that neural networks reduce the overall time required for implementation by a significant amount when compared with conventional methods. One of the major reasons that contribute to this advantage is that each network requires the solution of relatively simple set of equations to solve all kinds of problems while conventional methods may use more elaborate set of equations. Moreover, the performance of each proposed network includes the accuracy of outputs and the ease of use is satisfactory. With careful implementations, neural networks will be proficient to solve great number of structural engineering problems. On the other hand, it should be noted that satisfactory results from ANN are only available within the range of variation of input data of the training set.

5. Refrences

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